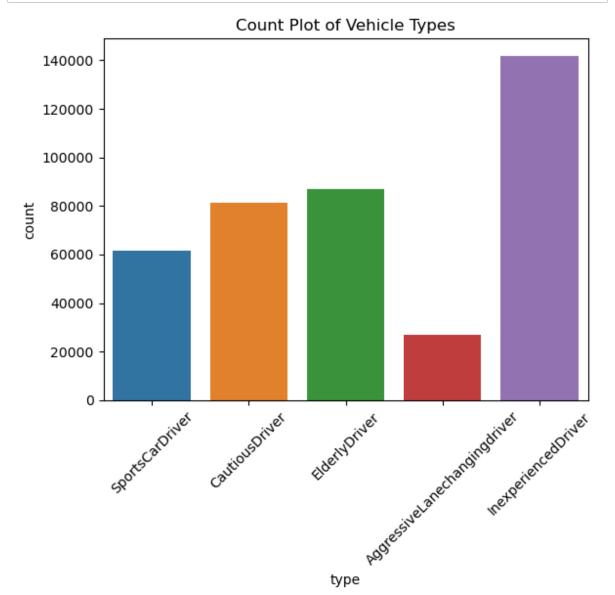
Driver Type Clasification(Supervised)-FCD Output

In [1]:	import pandas as pd									
In [2]:	<pre>fcd_df = pd.read_excel("C:/Users/saiko/OneDrive/Desktop/699/Task-7/fcd-output</pre>									
In [3]:	fcd_df									
Out[3]:		time	id	x	у	angle	type	speed	pos	lane
	0	0.0	f_0.0	-38.09	-4.80	90.00	SportsCarDriver	0.00	61.91	E0_0
	1	0.0	f_1.0	-57.03	-37.67	33.37	CautiousDriver	0.00	75.68	E5_0
	2	0.0	f_2.0	-33.33	-1.60	90.00	ElderlyDriver	0.00	66.67	E0_1
	3	0.0	f_3.0	357.14	4.80	270.00	AggressiveLanechangingdriver	0.00	42.86	E2_0
	4	0.0	f_4.0	241.15	21.32	215.86	AggressiveLanechangingdriver	0.00	98.24	E7_0
	398475	999.9	f_5.222	111.69	1.60	270.00	SportsCarDriver	0.00	102.38	E1_2
	398476	999.9	f_5.223	245.35	4.80	270.00	InexperiencedDriver	12.57	55.00	E3_1
	398477	999.9	f_5.224	158.14	4.80	270.00	SportsCarDriver	26.32	55.93	E1_1
	398478	999.9	f_5.225	335.19	1.60	270.00	ElderlyDriver	8.05	64.81	- E2_1
	398479	999.9	f_5.226	367.06	4.80	270.00	ElderlyDriver	0.04	32.94	E2_0
	398480 rows × 11 columns									
	4									•

Count Plot of Vehicle Types

```
In [5]: import seaborn as sns
import matplotlib.pyplot as plt

# Example of creating a count plot for the 'type' column
sns.countplot(data=fcd_df, x='type')
plt.title('Count Plot of Vehicle Types')
plt.xticks(rotation=45) # Rotate x-axis labels for better readability if need
plt.show()
```



```
In [6]: fcd_df['id'] = fcd_df['id'].str.replace(r'^f_', '', regex=True)
```

```
from sklearn.preprocessing import LabelEncoder
In [7]:
         # Initialize LabelEncoder
         label_encoder = LabelEncoder()
         # Encode categorical columns
         fcd_df['Type_encoded'] = label_encoder.fit_transform(fcd_df['type'])
         fcd_df['lane'] = label_encoder.fit_transform(fcd_df['lane'])
         fcd_df.drop(columns=['type'],inplace=True)
In [8]:
         fcd_df.drop(columns=['id'],inplace=True)
         fcd_df
In [9]:
Out[9]:
                   time
                                       angle speed
                                                       pos lane
                                                                 slope
                                                                       acceleration Type_encoded
                            Х
                        -38.09
                                -4.80
                                       90.00
                                               0.00
                                                     61.91
                                                             34
                                                                              0.00
               1
                    0.0
                       -57.03 -37.67
                                       33.37
                                               0.00
                                                     75.68
                                                             47
                                                                    0
                                                                              0.00
                                                                                               1
               2
                                                                                               2
                    0.0
                       -33.33
                                -1.60
                                       90.00
                                               0.00
                                                     66.67
                                                                    0
                                                                              0.00
                                                             35
                    0.0 357.14
                                 4.80
                                      270.00
                                               0.00
                                                     42.86
                                                              5
                                                                    0
                                                                              0.00
                                                                                               0
                                21.32 215.86
                                               0.00
                                                     98.24
                                                                                               0
                    0.0
                        241.15
                                                             49
                                                                    0
                                                                              0.00
          398475 999.9
                       111.69
                                 1.60 270.00
                                               0.00
                                                    102.38
                                                              4
                                                                    0
                                                                              0.00
                                                                                               4
          398476 999.9 245.35
                                 4.80 270.00
                                              12.57
                                                     55.00
                                                              7
                                                                    0
                                                                              0.80
                                                                                               3
          398477 999.9 158.14
                                 4.80 270.00
                                              26.32
                                                     55.93
                                                                              -3.12
                                                                                               4
```

8.05

0.04

64.81

32.94

6

5

0

0

1.15

0.22

2

398480 rows × 10 columns

398478 999.9 335.19

398479 999.9 367.06

Random Forest(ensemble Method)

1.60 270.00

4.80 270.00

```
import pandas as pd
In [20]:
         from sklearn.model_selection import train_test_split
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.metrics import accuracy_score
         # Assuming 'df' is your DataFrame containing the data
         # Features (X) and target variable (y)
         X = fcd_df.drop('Type_encoded', axis=1) # Features
         y = fcd_df['Type_encoded'] # Target variable
         # Split the data into training and testing sets (adjust test_size and random_s
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
         # Initialize the classifier (you can use any other classifier of your choice)
         clf_rand = RandomForestClassifier(n_estimators=200, random_state=42)
         # Fit the classifier on the training data
         clf_rand.fit(X_train, y_train)
         # Predict on the test data
         y_pred = clf_rand.predict(X_test)
         # Calculate accuracy
         accuracy = accuracy_score(y_test, y_pred)
         print(f"Accuracy: {accuracy}")
```

Accuracy: 0.9597470387472395

In []:

```
import pandas as pd
In [ ]:
        from sklearn.model selection import train test split
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.metrics import accuracy_score
        # Assuming 'df' is your DataFrame containing the data
        # Features (X) and target variable (y)
        X = fcd_df.drop('Type_encoded', axis=1) # Features
        y = fcd_df['Type_encoded'] # Target variable
        # Split the data into training and testing sets (adjust test size and random s
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
        from sklearn.model selection import GridSearchCV
        # Define the parameters for tuning
        param grid = {
            'n_estimators': [50, 100, 200]
              'max_depth': [None, 10, 20, 30],
              'min_samples_split': [2, 5, 10],
               'min_samples_leaf': [1, 2, 4]
        }
        # Create the GridSearchCV object
        grid_search = GridSearchCV(RandomForestClassifier(random_state=42), param_grid
        # Fit the grid search to the data
        grid_search.fit(X_train, y_train)
        # Get the best parameters and the best estimator
        best_params = grid_search.best_params_
        best_estimator = grid_search.best_estimator_
        print(f"Best Parameters: {best_params}")
        # Use the best estimator for prediction
        y_pred_tuned = best_estimator.predict(X_test)
        # Calculate accuracy
        accuracy_tuned = accuracy_score(y_test, y_pred_tuned)
        print(f"Tuned Model Accuracy: {accuracy_tuned}")
        report_data = classification_report(y_test, y_pred_tuned)
        print(report_data)
```

```
In [ ]: fcd_df
```

```
In [ ]: import numpy as np
        from keras.models import Sequential
        from keras.layers import LSTM, Dense
        from sklearn.preprocessing import LabelEncoder
        from tensorflow.keras.utils import to categorical
        from sklearn.model selection import train test split
        # Assuming X train and y train are already defined and properly scaled
        # Features (X) and target variable (y)
        X = fcd_df.drop('type', axis=1) # Features
        y = fcd df['type'] # Target variable
        # Split the data into training and testing sets (adjust test_size and random_s
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
        # Encode the labels to integers
        label_encoder = LabelEncoder()
        encoded y train = label encoder.fit transform(y train)
        encoded_y_test = label_encoder.transform(y_test)
        # Convert integers to dummy variables (i.e., one-hot encoded)
        dummy_y_train = to_categorical(encoded_y_train)
        dummy_y_test = to_categorical(encoded_y_test)
        # Reshape input to be [samples, time steps, features] which is required for L
        # Since your data doesn't have a time step, we can treat each row as 1 time st
        X_train_reshaped = np.reshape(X_train, (X_train.shape[0], 1, X_train.shape[1])
        X_test_reshaped = np.reshape(X_test, (X_test.shape[0], 1, X_test.shape[1]))
In [ ]: X_train_reshaped.shape
In [ ]: |dummy_y_train.shape
In [ ]: | from tensorflow.keras.optimizers import Adam
        # Define LSTM model
        model = Sequential()
        model.add(LSTM(50, input_shape=(X_train_reshaped.shape[1], X_train_reshaped.sl
        model.add(Dense(dummy y train.shape[1], activation='softmax'))
        # Compile the model
        model.compile(loss='categorical_crossentropy', optimizer=Adam(), metrics=['ac
        # Fit the model
        model.fit(X_train_reshaped, dummy_y_train, epochs=100, batch_size=32, validat
        # Evaluate the model
        scores = model.evaluate(X_test_reshaped, dummy_y_test, verbose=0)
        print("Accuracy: %.2f%%" % (scores[1]*100))
```

```
In [ ]:
    # Evaluate the model on the test data
    _, accuracy = model.evaluate(X_test, y_test)
    print(f"Accuracy: {accuracy}")
```

DNN Model

```
import pandas as pd
In [11]:
         from sklearn.model selection import train test split
         from sklearn.preprocessing import StandardScaler
         from sklearn.metrics import accuracy_score
         from tensorflow.keras.models import Sequential
         from tensorflow.keras.layers import Dense, Dropout
         from tensorflow.keras import regularizers
         from tensorflow.keras.utils import to categorical
         # Assuming 'fcd_df' is your DataFrame containing the data
         # Features (X) and target variable (y)
         X = fcd_df.drop('Type_encoded', axis=1) # Features
         y = fcd_df['Type_encoded'] # Target variable
         # Convert y to categorical (one-hot encoded)
         y = to_categorical(y)
         num classes = 5
         # Split the data into training and testing sets
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
         # Standardize features
         scaler = StandardScaler()
         X train = scaler.fit transform(X train)
         X_test = scaler.transform(X_test)
         # Define the Deep Neural Network model with L2 regularization and dropout
         model = Sequential()
         model.add(Dense(128, input_dim=X_train.shape[1], activation='relu', kernel_re
         model.add(Dropout(0.5))
         model.add(Dense(64, activation='relu', kernel_regularizer=regularizers.12(0.0)
         model.add(Dropout(0.5))
         model.add(Dense(32, activation='relu', kernel regularizer=regularizers.12(0.0)
         model.add(Dropout(0.5))
         model.add(Dense(num_classes, activation='softmax')) # For multi-class classi
         # Compile the model
         model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['ac
         # Fit the model on the training data
         model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_test
         # Evaluate the model on the test data
         _, accuracy = model.evaluate(X_test, y_test)
         print(f"Accuracy: {accuracy}")
```

```
Epoch 1/10
9962/9962 [============ ] - 17s 2ms/step - loss: 1.3797 - a
ccuracy: 0.4311 - val_loss: 1.3037 - val_accuracy: 0.4449
9962/9962 [=========== ] - 15s 1ms/step - loss: 1.3145 - a
ccuracy: 0.4410 - val_loss: 1.2915 - val_accuracy: 0.4472
Epoch 3/10
9962/9962 [============= ] - 14s 1ms/step - loss: 1.3073 - a
ccuracy: 0.4420 - val_loss: 1.2914 - val_accuracy: 0.4447
Epoch 4/10
9962/9962 [========== ] - 15s 2ms/step - loss: 1.3043 - a
ccuracy: 0.4423 - val_loss: 1.2825 - val_accuracy: 0.4493
Epoch 5/10
ccuracy: 0.4427 - val_loss: 1.2853 - val_accuracy: 0.4477
Epoch 6/10
9962/9962 [============ ] - 15s 1ms/step - loss: 1.3020 - a
ccuracy: 0.4422 - val loss: 1.2852 - val accuracy: 0.4466
ccuracy: 0.4429 - val_loss: 1.2781 - val_accuracy: 0.4480
Epoch 8/10
9962/9962 [============ ] - 14s 1ms/step - loss: 1.2996 - a
ccuracy: 0.4425 - val_loss: 1.2776 - val_accuracy: 0.4485
Epoch 9/10
9962/9962 [=========== ] - 14s 1ms/step - loss: 1.3002 - a
ccuracy: 0.4424 - val_loss: 1.2863 - val_accuracy: 0.4447
Epoch 10/10
9962/9962 [============ ] - 15s 1ms/step - loss: 1.2993 - a
ccuracy: 0.4429 - val loss: 1.2788 - val accuracy: 0.4480
accuracy: 0.4480
Accuracy: 0.44802749156951904
```

Gaussian Naive Bayes

```
from sklearn.model_selection import train_test_split
In [12]:
         from sklearn.naive bayes import GaussianNB
         from sklearn.metrics import accuracy_score
         from sklearn.preprocessing import MinMaxScaler
         import pandas as pd
         # Assuming 'fcd_df' is your DataFrame containing the data
         # Features (X) and target variable (y)
         X = fcd_df.drop('Type_encoded', axis=1) # Features
         y = fcd df['Type encoded'] # Target variable
         # Split the data into training and testing sets
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
         # Initialize the MinMaxScaler and fit-transform the training data
         scaler = MinMaxScaler()
         X_train = scaler.fit_transform(X_train)
         # Transform the test data using the same scaler
         X_test = scaler.transform(X_test)
         # Initialize the Gaussian Naive Bayes classifier
         clf = GaussianNB()
         # Fit the classifier on the training data
         clf.fit(X_train, y_train)
         # Predict on the test data
         y pred = clf.predict(X test)
         # Calculate accuracy
         accuracy = accuracy_score(y_test, y_pred)
         print(f"Accuracy: {accuracy}")
```

Accuracy: 0.41406093153985146

KNN-Model

```
In [13]: # Import necessary libraries
         import pandas as pd
         from sklearn.model_selection import train_test_split
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.preprocessing import StandardScaler
         from sklearn.metrics import accuracy score
         # Features (X) and target variable (y)
         X = fcd df.drop('Type encoded', axis=1) # Features
         y = fcd df['Type encoded'] # Target variable
         # Split the dataset into training and testing sets
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rand
         # Standardize features by removing the mean and scaling to unit variance
         scaler = StandardScaler()
         X_train = scaler.fit_transform(X_train)
         X_test = scaler.transform(X_test)
         # Initialize the k-NN classifier
         k = 5 # You can change this value as needed
         knn = KNeighborsClassifier(n_neighbors=k)
         # Fit the model on the training data
         knn.fit(X_train, y_train)
         # Predict the labels for the test set
         y_pred = knn.predict(X_test)
         # Calculate the accuracy of the model
         accuracy = accuracy_score(y_test, y_pred)
         print(f'Accuracy of the k-NN model: {accuracy:.2f}')
```

Accuracy of the k-NN model: 0.86

Best Model Performance on unseen data(New Simulation data)

```
In [14]: fcd_df_New = pd.read_excel("C:/Users/saiko/OneDrive/Desktop/699/Task-7/fcd-out
In [15]: fcd_df_New['id'] = fcd_df_New['id'].str.replace(r'^f_', '', regex=True)
```

```
from sklearn.preprocessing import LabelEncoder
In [16]:
          # Initialize LabelEncoder
          label_encoder = LabelEncoder()
          # Encode categorical columns
          fcd df New['Type_encoded'] = label_encoder.fit_transform(fcd_df_New['type'])
          fcd_df_New['lane'] = label_encoder.fit_transform(fcd_df_New['lane'])
          fcd df_New.drop(columns=['type'],inplace=True)
In [17]:
          fcd_df_New.drop(columns=['id'],inplace=True)
          import pandas as pd
In [18]:
          # Assuming df is your DataFrame
          # Shuffle the rows using sample() function
          shuffled_df = fcd_df_New.sample(frac=1, random_state=42) # frac=1 shuffles t
          # Reset the index if needed
          shuffled df.reset index(drop=True, inplace=True)
          shuffled_df
In [19]:
Out[19]:
                   time
                             X
                                 y angle speed
                                                  pos lane slope acceleration Type_encoded
                   50.3
                          1.65 -1.6
                                     90.0
                                            7.35
                                                  9.52
                                                                0
                                                                         0.93
                0
                                                         46
                                                                                         3
                1 587.9
                        -14.82 -1.6
                                     90.0
                                            9.65 85.18
                                                                0
                                                                         0.90
                                                         35
                                                                                         3
                2 440.3
                         24.21 4.8
                                    270.0 14.03 58.54
                                                         9
                                                                0
                                                                         0.91
                                                                                         1
                3 834.9
                         58.19 -4.8
                                     90.0
                                           13.61 66.06
                                                         45
                                                                0
                                                                         0.69
                                                                                         2
                 196.8
                         81.08 4.8 270.0
                                           21.35
                                                  1.67
                                                         9
                                                                0
                                                                         0.53
                                                                                         3
                            ...
                                       ...
                                                         ...
                                                               ...
                                                                           ...
           398471 651.7 108.07 -1.6
                                     90.0
                                           21.03 16.17
                                                                         2.95
                                                         38
                                                                0
                                                                                         4
           398472 918.4 312.23 -4.8
                                     90.0
                                           18.98
                                                  5.85
                                                                         0.28
                                                         39
                                                                0
                                                                                         3
           398473 333.6
                         52.71 -1.6
                                     90.0
                                           14.44 60.58
                                                         46
                                                                0
                                                                         0.85
                                                                                         3
           398474 370.9 139.56 -4.8
                                     90.0
                                           17.69 47.66
                                                         37
                                                                0
                                                                         0.40
                                                                                         2
           398475 308.6 191.37 8.0 270.0
                                                         2
                                                                         0.56
                                          13.13 22.70
                                                                n
                                                                                         3
```

398476 rows × 10 columns

Random Forest Evaluation

```
In [22]: import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Assuming 'df' is your DataFrame containing the data

# Features (X) and target variable (y)

X = shuffled_df.drop('Type_encoded', axis=1) # Features
y = shuffled_df['Type_encoded'] # Target variable

# Predict on the test data
y_pred = clf_rand.predict(X)

# Calculate accuracy
accuracy = accuracy_score(y, y_pred)
print(f"Accuracy: {accuracy}")
```

Accuracy: 0.5632560053804997

In []: